

MODELS FOR HANDLING UNCERTAINTY IN FETAL HEART RATE AND ECG ANALYSIS

E. C. Ifeachor¹, J. S. K. Curnow², N. J. Outram³ and J. F. Skinner¹

¹SMART Medical Systems Group, Centre for Communications, Networks and Information Systems, University of Plymouth, UK, ²Plymouth Derriford Hospital, UK and ³Neovanta AB, Sweden

Abstract- Methods for handling imprecision and uncertainty in computer-based analysis of fetal heart rate patterns and ECG wave shape during childbirth are presented. Computational intelligence models, based on fuzzy logic techniques, that explicitly handle the imprecision and uncertainty inherent in the data obtained during childbirth and methods of interpreting the data are proposed. The ability to handle imprecision and uncertainty in clinical data and method of interpretation is vital to remove a key obstacle in electronic fetal monitoring.

Keywords - Electronic fetal monitoring, fetal heart rate, cardiotocogram, fetal ECG, fuzzy logic, computational intelligence models.

I. INTRODUCTION

Methods for handling imprecision and uncertainty in computer-based analysis of fetal heart rate patterns and electrocardiogram (ECG) wave shape during labour are described. Childbirth is a critical period for the fetus and mother. The outcome of labour is normally good, but sometimes problems occur that may lead to injury (e.g. fetal brain damage) or even death [1,2]. Electronic fetal monitoring, introduced in the late 1960's [3], was expected to improve patient care, but this has not yet happened. The most common monitoring method is based on a continuous trace of the fetal heart rate pattern and maternal contractions, known as the cardiotocogram (CTG). Difficulties in the interpretation of the CTG have led to unnecessary medical interventions (e.g. Caesarean sections and forceps deliveries) [2] and a failure to intervene when necessary [1] (which can lead to preventable injuries and deaths). These problems have led to the development of a number of computerized systems to assist with the analysis and interpretation of CTG [4-10]. However, despite over two decades of development no system is in widespread routine clinical practice.

Progress in computerized CTG analysis has been impeded by several factors. First, there are significant, inherent problems of imprecision and uncertainty in the clinical data and the interpretation methods used [11]. These problems have yet to be addressed in computerized CTG systems. Secondly, the CTG does not contain sufficient information for accurate assessment of the fetal condition [12]. Additional information may be obtained by a proper analysis of changes in the fetal electrocardiogram (ECG), but the problems of uncertainty and imprecision also exist in fetal ECG analysis.

We have proposed computational intelligence models, based on fuzzy logic techniques, to explicitly handle the imprecision and uncertainty in clinical knowledge and data.

In this paper, we describe the models and their application to fetal heart rate and ECG analysis. In sections II and III, respectively, the development of the models for CTG and ECG analysis will be presented. In each case, we start with a highlight of the nature and sources of imprecision and uncertainty to provide the basis for designing the fuzzy models.

II. MODELLING UNCERTAINTY AND IMPRECISION IN FETAL HEART RATE ANALYSIS

A. Uncertainty and imprecision in fetal heart rate analysis

Over the last three decades, several CTG features have been identified and basic guidelines for their interpretation established to provide clinicians with a method of predicting the condition of the fetus and outcome of labour [3, 13, 14]. The five key features in the CTG are heart rate *baseline*, *acceleration* and *deceleration* in heart rate, heart rate *variability* and *uterine contractions*, see Figure 1.

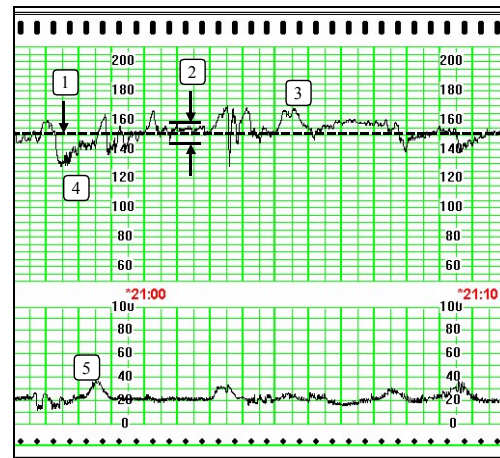


Fig. 1. An example 15 minute segment of cardiotocogram - fetal heart rate (top trace) and uterine contraction (bottom trace) showing the key features. 1) baseline 2) variability, 3) acceleration, 4) deceleration and 5) contractions

In CTG analysis systems, each feature is identified and then classified using rules derived from the guidelines [13], see for example Tables I and II. The problem is that the guidelines are based on empirical observations and lacks precision because of the high false positive abnormality rate of the CTG. This has led to a situation where two "experts" can give different interpretations of the same CTG trace. Further, there are no precise expected outcome for a given set of features even when interpreted consistently. A reason for

Report Documentation Page

Report Date 25 Oct 2001	Report Type N/A	Dates Covered (from... to) -
Title and Subtitle Models for Handling Uncertainty Fetal Heart Rate and ECG Analysis		Contract Number
		Grant Number
		Program Element Number
Author(s)	Project Number	
	Task Number	
	Work Unit Number	
Performing Organization Name(s) and Address(es) SMART Medical Systems Group Center for Communications, Networks and Information Systems University of Plymouth, UK		Performing Organization Report Number
Sponsoring/Monitoring Agency Name(s) and Address(es) US Army Research, Development & Standardization Group (UK) PSC 802 Box 15 FPO AE 09499-1500		Sponsor/Monitor's Acronym(s)
		Sponsor/Monitor's Report Number(s)
Distribution/Availability Statement Approved for public release, distribution unlimited		
Supplementary Notes Papers from 23rd Annual International Conference of the IEEE Engineering in Medicine and Biology Society, October 25-28, 2001, held in Istanbul, Turkey. See also ADM001351 for entire conference on cd-rom., The original document contains color images.		
Abstract		
Subject Terms		
Report Classification unclassified	Classification of this page unclassified	
Classification of Abstract unclassified	Limitation of Abstract UU	
Number of Pages 7		

this is that the CTG features alone are insufficient to give an accurate indication of fetal condition. More clinical information is needed for a realistic interpretation of data. In addition, methods used to identify CTG features are inexact and vary from system to system.

Most current computerized intelligent CTG systems use crisp models [8-10, 14], despite the imprecision and uncertainties in the clinical knowledge and data. An example of typical statements that describe the interpretation of CTG features is: "If there is a *baseline bradycardia* and the *variability* is *quite low* and there are *no accelerations* then I would consider the trace to be *very abnormal*." Such a statement might be represented in a crisp model using a rule of the form:

IF *Baseline* < 90 AND *Variability* < 5 AND *Accelerations* = 0 THEN CTG is *Severely Abnormal*

The crisp rule does not capture the obvious vagueness inherent in the clinician's model of CTG interpretation. Further, as is evident from the first columns of Table 1 and 2, small changes in the CTG features can produce a different classification. Such an abrupt change in classification does not represent clinical reality. Although the classification boundaries are precise (see for example, the left hand column in Table 1), an experienced clinician would take adequate care in interpreting CTGs that are near the boundaries because of the normal physiological variations and differences between fetuses. The problem in crisp CTG expert systems is that an imprecise clinical model is represented as a precise computer model. What is required is a model that caters for the inherently vague domain knowledge and imprecise clinical data to enhance the robustness and performance of CTG based electronic fetal monitoring systems.

TABLE I Classification of baseline heart rate	
Baseline (beats per minute)	Linguistic Classification
<90	Bradycardia
90-109	Slight Bradycardia
110-159	Normal
160-180	Slight Tachycardia
>180	Tachycardia

TABLE II Classification terms for heart rate variability	
Variability (beats per minute)	Linguistic Classification
<2	Absent
2-5	Reduced
6-25	Normal
>25	Increased

A variety of different techniques may be used to handle the imprecision and uncertainty in CTG and ECG analysis, but fuzzy logic and fuzzy set theory offer the most

comprehensive and flexible framework to address the problems [15]. In particular, we have found that they are suited to modeling human clinical decision making and behaviour. In addition, the parameters of the fuzzy model (e.g. fuzzy sets and fuzzy rules) are accessible to clinicians in a natural form and this is an important factor in the successful development of the model.

B. Fuzzy model for CTG analysis

The two key parameters of a fuzzy model are the fuzzy sets and fuzzy rules. The main issues in the design of the fuzzy sets for CTG analysis include the choice of the shape of membership functions for the sets, set names, number of sets, position and universe of discourses for the sets. The fuzzy model presented here is for front-end CTG analysis. The existing crisp system is used as a starting point in the development of the model as it has captured the essential clinical knowledge [8,16].

The fuzzy sets are used to represent the four features of the CTG (baseline, variability, accelerations and decelerations) and the CTG segment. They model the linguistic classification of the features and the classification of CTG segments. The linguistic terms and classifications for the CTG features are:

Baseline {*Bradycardia, Slight Bradycardia, Normal, Slight tachycardia, Tachycardia*}
Variability {*Absent, Reduced, Normal, Increased*}
Accelerations {*Absent, Present*}
Decelerations {*Absent, Present, Severe*}

The linguistic terms for the CTG features are a natural choice for fuzzy set names. In the case of Baseline and Variability, the widths and positions of the sets are determined by the end points in the clinical guidelines in Tables I and II. In the case of Acceleration and Deceleration, the widths and positions of the sets are arbitrary as they have no clinical significance. Sigmoid curves are used for the membership functions as they represent clinical model for CTG analysis more realistically than triangular functions.

There are two sets of rules for CTG analysis:

- A set of rules for classifying each of the four CTG features - *Baseline, Variability, Accelerations* and *Deceleration*.
- A rule set to provide an overall classification for the segment. This rule set was derived from rules used in the crisp model. The crisp rule set was considered extremely inefficient and so the ID3 rule induction algorithm [17] was used to reduce them from 120 to 33 without altering the same performance. An example of this type of rule is: "IF Baseline is Normal AND Deceleration is Severe AND Variability is Absent THEN Segment is Severe Abnormal".

The fuzzy model that incorporates the fuzzy sets and fuzzy rules is depicted in Figure 2. The features of heart rate and contractions are first identified using numerical algorithms and then fuzzified. The fuzzified feature set is then used to produce a segment classification using the second rule set [18]. Max-prod inference is used to apply the rules. The segment classification output set is defuzzified using the centroid method to give a scalar value (0 – 100), to provide an overall index of the segment abnormality.

C. Evaluation of the fuzzy model for CTG analysis

The fuzzy model was used to process CTG traces and its performance compared to that of the crisp model and to four clinical experts. Ninety five 15-minute segments of CTG traces were chosen from a data base of approximately 6, 500 hours of digitized CTG data. The segments selected were not used in the development of the crisp or fuzzy models and contained as many combinations of CTG features as possible. 15-minute segments were used as this was considered to be the minimum clinically useful length of trace. The segments were independently evaluated by four clinicians all with significant experience of CTG interpretation. The reviewers were asked to analyze each 15-minute segment and give a score between 0 and 39, indicating how normal or abnormal they considered the heart rate pattern to be (see Table III).

TABLE III

Protocol used by reviewers to score the CTG traces. This shows the relationship between the scores and linguistic classification of the trace.

Score	Linguistic Classification
0-9	Normal
10-19	Intermediate
20-29	Abnormal
30-39	Severely abnormal

Results. The CTG traces were ranked by score for each reviewer and by the output scores derived from the crisp and fuzzy models. Table 4 shows the agreement in case ranking between the models and reviewers, based on Spearman rank correlation statistic, with correction for tied ranks [18]. Although absolute scoring of CTGs should be interpreted with care, the results show that the agreement of the fuzzy system with each of the reviewers, particularly the two practicing clinicians (A to C), is higher than that of the crisp model. The result suggests that, potentially, there are benefits in the use of fuzzy techniques to improve the performance of crisp CTG systems. The output of the fuzzy model has a high correlation with that of the crisp model. This is likely to be because the current fuzzy model is an evolution of the crisp model and use the same rules. It is interesting to note that the crisp model has the highest correlation with expert C who was involved in its initial development. The three practicing clinicians A, B and C, have a high agreement in

ranking. This implies that common criteria are being used for the relative assessment of the traces, but the assignment of an overall linguistic description to a trace may be inconsistent. Reviewer D has a much lower agreement in ranking than the other reviewers. It is interesting to note that this reviewer, while experienced in CTG assessment, is not involved in day to day management of labour in a clinical setting. It is likely that different criteria for assessment are being used, which may not be directly applicable for clinical use.

TABLE IV

Spearman rank correlation of segment ranking between reviewers, the crisp and fuzzy models.

Reviewer	A	B	C	D	Crisp	Fuzzy
A	-	0.80	0.37	0.54	0.51	0.73
B	0.80	-	0.59	0.54	0.50	0.67
C	0.37	0.59	-	0.36	0.46	0.50
D	0.54	0.54	0.36	-	0.55	0.59
Crisp	0.51	0.50	0.46	0.55	-	0.82
Fuzzy	0.73	0.67	0.50	0.59	0.82	-

During the study, it was found that the behaviour of the crisp model depended on the starting point on the CTG trace and hence the relative positions of the segments. Small shifts in the starting position could lead to significant differences in the classification of the segment. The sequence of segment classifications is crucial to the overall assessment of a CTG record in practice and hence could lead to significant differences in the recommended clinical action. To quantify the behaviour of the models, the starting point for analysis was varied by up to 30 seconds. It was found that the crisp model had a classification error of 5.67% compared to 1.42% for the fuzzy model.

III. MODELLING UNCERTAINTY AND IMPRECISION IN ECG ANALYSIS

A. Uncertainty and imprecision in ECG analysis

The fetal ECG may be used, in association with the CTG features, to obtain an enhanced assessment of the condition of the fetus during labour [12, 19]. The fetal ECG can be collected by scalp electrodes from the second stage of labour and is thought to provide a more direct indication of fetal well being. However, interpretation of fetal ECG features is difficult, particularly in real time at the bedside. Figure 4 illustrates some of the important features of the ECG, including the ST waveform and the R-to-R intervals from which the fetal heart rate pattern. Changes in the ST waveform may be quantified as a ratio of the amplitude of the T wave to that of the QRS, known as the T/QRS ratio, and the ST area. [12, 19].

A major source of uncertainty and imprecision is the clinical knowledge itself. Much of the knowledge is qualitative and based on experience and observations which cannot be easily verified experimentally. The imprecision in the knowledge is evident from the following two rules derived from the clinical guidelines [20]: “IF CTG is *Intermediate* AND TQRS is *normal* THEN No Action; (2) IF CTG is *Abnormal* and TQRS is *high* and there are no *significant changes* in the TQRS values THEN take FBS or deliver”. In addition, the classification of the ECG features suffers from threshold problems (e.g. abrupt jumps in decision boundaries). Errors in the measured features, e.g. due to poor signal quality, are a further source of uncertainty [21]. These can lead to false or missed changes in the ECG features. The natural variability of some of the features between fetuses can also lead to misinterpretation. A crisp model is clearly inappropriate for ECG analysis. We have used fuzzy logic to cater for the above problems and to capture expert knowledge in a more natural form. The use of fuzzy logic makes the model less sensitive to noise or errors and natural variability in the data.

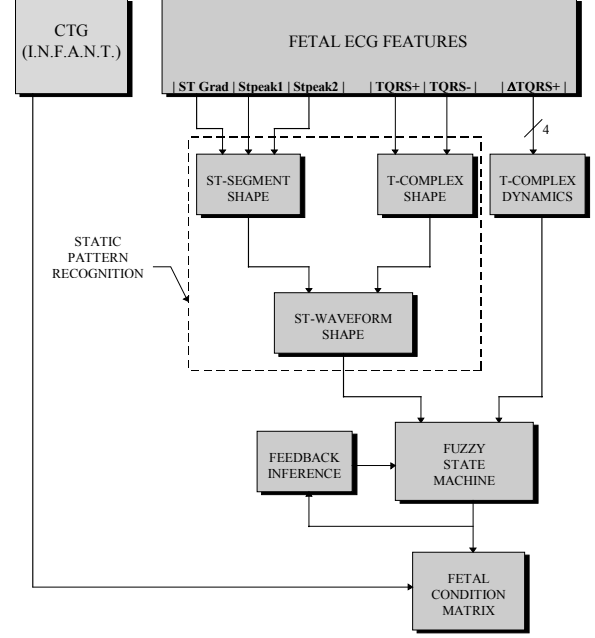


Fig. 4. Fuzzy model for ECG analysis

B. Fuzzy model for fetal ECG analysis

As with the model for CTG analysis, the two primary design parameters in the fuzzy ECG model are the fuzzy sets and the fuzzy rules. In the design of fuzzy sets, it is necessary to first describe the features and facts using linguistic variables. The important linguistic terms used in the clinical guidelines [21] are given below. The words in brackets are the different categories.

- *T/QRS Ratio*: {Constant, Increasing, Rising, Rapidly Increasing, Negative, Positive, High, Normal}
- *ST Waveform*: {Normal, Depressed, Negative, Elevated, Raised, Bi-Phasic, Changing, Acute change}
- *CTG Pattern*: {Normal reactive, Intermediate, Abnormal, Normal, Pre-terminal}
- *Heart Rate Declarations*: {Persistent, Late, Variable, Present, Not Present}
- *Baseline Heart Rate*: {Increased, bradycardia, Low, tachycardia, High, Normal, Rapid return}
- *Heart-rate Variability*: {Increased, Decreased, Normal, Undulating}

Some of the terms imply instantaneous events (e.g. *High T/QRS ratio*) and others imply time (e.g. *Rapidly Increasing T/QRS ratio* or *constantly elevated ST waveform*). To handle these, new fuzzy variables have been created as follows:

- $\Delta T/QRS(20)$: {Low, Medium High} //Change in T/QRS over 20 minutes
- $\Delta T/QRS(15)$: {Low, Medium High} //Change in T/QRS over 15 minutes
- $\Delta T/QRS(10)$: {Low, Medium High} //Change in T/QRS over 10 minutes
- $\Delta T/QRS(5)$: {Low, Medium High} //Change in T/QRS over 5 minutes
- *STSegment*: {Normal, Biphasic, Depressed, Elevated}
- *Tcomplex*: {Negative, Normal, Elevated, Highly Elevated}

In the design of the fuzzy sets, we have used the linguistic terms as set names to keep close to the language of the clinicians. Triangular membership functions are used for simplicity. Parameters of the fuzzy sets, such as set positions and universe of discourses, are derived from the clinical guidelines and through discussions with clinical experts.

The fuzzy rules are derived from the clinical guidelines and from extensive formal and informal consultation with expert clinicians. There are four categories of rules as follows:

- Rules for assessing the quality of ECG data. Fetal ECG features are susceptible to distortion and need to be interpreted in proper context. The rules are used to provide an index of data quality, e.g. the severity of baseline shifts in the data.
- Rules for CTG analysis and interpretation. ECG features can only be properly interpreted if this is carried out in association with CTG analysis. At present the rules for CTG analysis are provided by our crisp system [8, 16], but in future these will come from the fuzzy CTG analysis model (see section II).

- Rules for Static Pattern Recognition – These are for the recognition and classification of important changes in the T complex shape and ST shape.
- Rules for Dynamic Pattern Recognition – These are rules for managing the progressive changes in ECG wave shape and for keeping track of past events.

The fuzzy model that embodies the fuzzy sets and rules above is depicted in Figure 4. The two bottom modules in the model (i.e. the fuzzy state machine and fetal condition matrix), play an important role in the dynamic pattern analysis of the ECG. During labour different sequences of events occur which can modify the way the expert interprets the instantaneous features. A fuzzy state model is proposed to represent and model the expert strategy for handling sequences of events in the course of labour, see Figure 5 [19]. Each state, represented by a circle, has a full set of rules associated with it. During the first stages of monitoring (the Entry State) a labour may be regarded as normal unless there is a prior knowledge to suggest otherwise. When a significant, new piece of information becomes available, a change of state will occur (e.g. State C) and the rules change.

The outcome of ECG analysis and the recommended action may be summarized in the form of a matrix (see Figure 6). Each element of the matrix produces a truth value for each of the conditions which can be de-fuzzified to a single point on a fuzzy condition map. The fetal Condition Matrix (FCM) provides a summary of the current fetal state at a glance. It is directly related to the clinical guidelines and is one which the midwives are familiar. This is an effective and simple analogue display device. Examples of the use of the fetal condition map in ECG analysis are given in Figures 7(a) and (b). Figure 7(a) is a typically normal case where the T/QRS ratio is constantly below 0.24 and the CTG is perfectly normal. Figure 7(b) is a perfectly normal case until the baseline heart-rate drops and stayed at 60bpm (abnormal CTG). The condition of the fetus is shown as a ‘moving point’ on the fetal condition matrix.

IV. DISCUSSION AND CONCLUSIONS

We have presented two fuzzy logic models for CTG and ECG analysis to handle the imprecision and uncertainty in the clinical data and knowledge during labour. The model for CTG analysis was compared to existing crisp model and initial results indicate that the fuzzy logic approach gives improved performance.

The fuzzy ECG model includes a method, based on finite state machine concepts, for handling the sequences of events during the course of labour, and adds memory to the model. This is an important aspect of the model as there are many situations during labour in which the expert's interpretation of the CTG is informed by previous events and their sequence. These include the following:

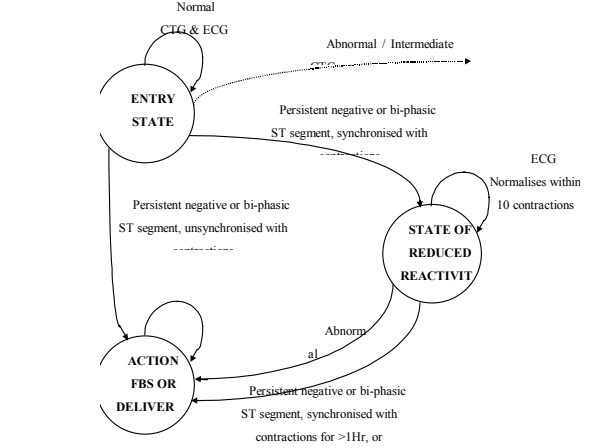


Fig. 5. Fuzzy state machine used to represent and recall events during labour

ST Waveform \ CTG	Normal	High and Stable	Negative or Rising
Normal	A No Action	B No Action	C FBS ¹ or Deliver
Intermediate	D No Action	E FBS or Deliver ⁴	F Deliver ²
Abnormal	G FBS or Deliver ⁴	H Deliver	I Deliver ³

Fig. 6 Fetal condition matrix used to guide clinicians

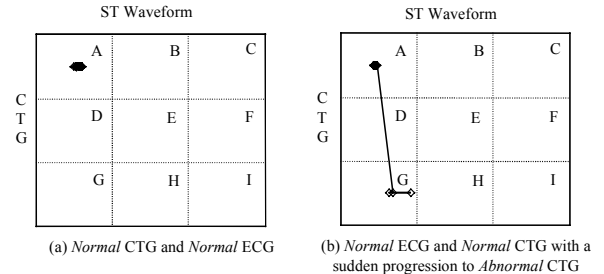


Fig. 7 Examples of fetal condition map

- An individual abnormal event is only short lasting, so its validity is in question.
- An event is only partially true - i.e. suspicious but not marked enough to warrant action.
- An event has occurred before, therefore adding to the belief that it is genuine and not noise.

- A different but possibly abnormal event had previously occurred.
- A similar pattern occurred in a previous labour.

A simple, but effective visual method for conveying the output of the fuzzy model for ECG analysis to clinicians proposed. The Fetal Condition Matrix is used to summarize the fetal state at a glance. The matrix is directly related to the clinical guidelines [20] and is one which the midwives are familiar with. A useful extension might be to set thresholds and trigger alarms when the fetal condition moves into a dangerous region in the fetal condition matrix. A simple linguistic approximation may be used in addition to the map to provide explanation.

The two fuzzy models have not yet been optimized. It may be necessary to tune their parameters to enhance performance using a suitable search/optimization algorithm [22]. The rules for CTG interpretation and for interpreting ECG need to be integrated.

ACKNOWLEDGMENT

The authors gratefully acknowledge the assistance of Professor Rosen, Dr Westgate and other clinicians for their assistance. We are also grateful to the UK EPSRC for funding to carry out the work

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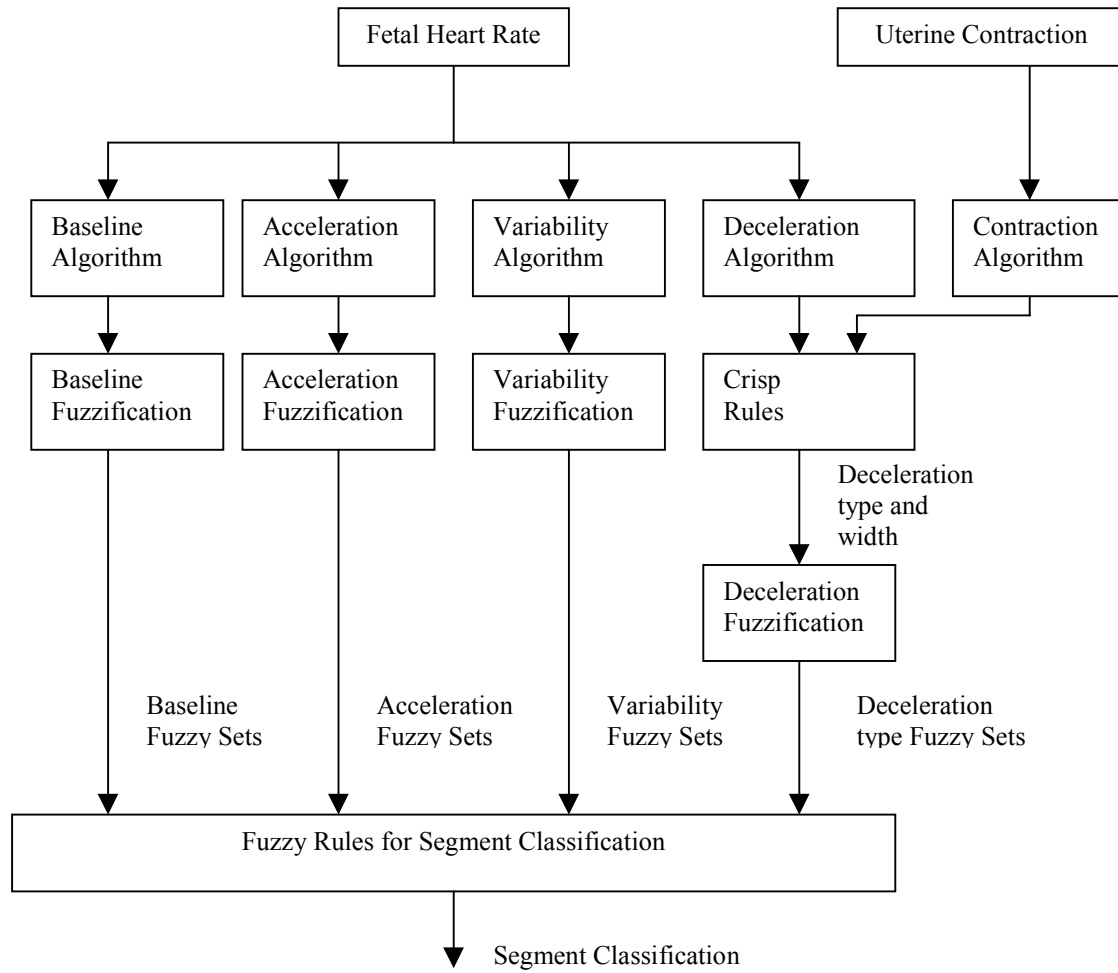


Fig. 2. Fuzzy model for CTG analysis

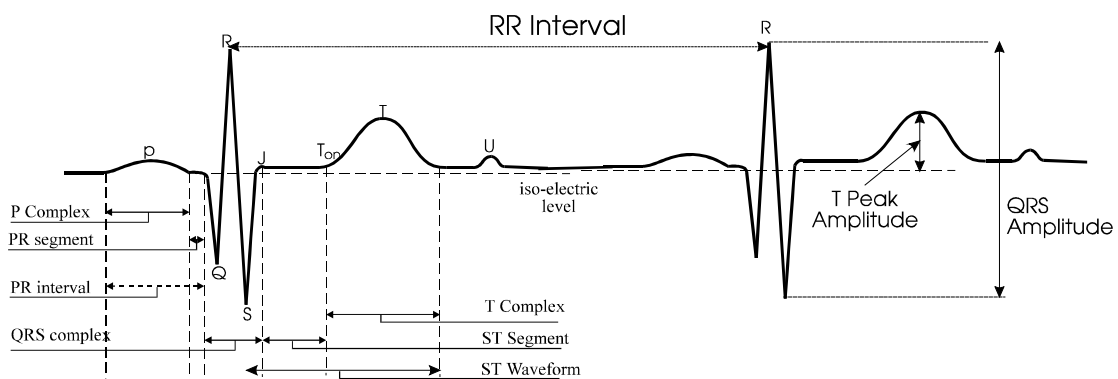


Fig. 3 Fetal electrocardiogram (ECG) showing key features